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Have you ever seen the rain? The causal impact of the weather situation and the season on survey participation in a multi-wave panel study

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This empirical study examines whether the weather situations during different seasons in which panel surveys are carried out have an impact on the timing and extent of survey participation. Based on considerations regarding the panellists' habits and their assessment of a participation's benefits and costs compared to alternative action, it is assumed that 'pleasant' weather diverts them from immediately participating in an online survey, while 'unpleasant' weather results in a higher degree of participation right after survey launch. The results of event history analysis based on longitudinal data from a multi-wave panel confirm these assumptions. Additionally, there seems to be an interaction between the season and the weather situation: 'pleasant' weather in spring results in a lower participation rate compared to surveys in summer, while – given the same weather situation – the participation rate is higher in autumn. Finally, it is evident that, regardless of the season, heavy rainfall at the beginning of the field period is most beneficial for conducting an online survey in terms of both rapid start and high rates of participation.

Keywords: Weather situation; season; online survey; panel study; event history analysis; survey participation

1 Introduction

Macro-dynamics such as weather situations, seasons, and regional opportunity structures have received only little attention in research on survey methods in general and in research on the survey participation of panellists in web-based online surveys in particular (Couper & Groves, 1996; Göritz, 2014; Potoski, Urbatsch, & Yu, 2015). However, Groves, Cialdini, and Couper (1992) for example stress that, aside from characteristics of the sampled target persons and attributes of the survey design, societal-level factors also affect the response behaviour of invited target persons in web-based surveys. In this vein, Keusch (2015, p. 185) concludes that, while only a few studies have empirically analysed the impacts of societal-level factors (such as the accepted legitimacy of sponsors and organizations conducting scientific surveys, the degree of social cohesion and integration, or the survey climate and survey fatigue due to the oversurveying of populations) on survey participation in general, corresponding knowledge about web-based online surveys is especially scarce (Groves et al., 1992). Furthermore, explanations of individual survey participation emphasize that regional opportunity structures and their characteristics affect participation and response rates as well. According to Groves and Couper (1998), large urban areas—inner-city areas in large metropolitan areas—generate lower response rates in social-scientific surveys than rural areas (Couper & Groves, 1996, p. 174). This may indicate that, compared to rural areas, urban areas provide more attractive opportunities that potentially divert target persons from taking part in social-scientific surveys. In addition, internet access—an essential precondition for participation in an online survey—differs between regions, with an obvious urban-rural divide (Fan & Yan, 2010, p. 136; Couper, 2000). Internet access is also unequally distributed among quartiers, correlating with the living standard of a quartier's residents. Finally, social integration and individual isolation related to regional opportunity structures are considered important for the explanation of response rates, i.e. the ratio of responding target persons out of the eligible target sample (Esser, 1986). According to the Social Isolation Hypothesis (Groves & Couper, 1998; see also: Saßenroth, 2013, p. 60), this means that socially less integrated and isolated individuals living mostly in urban areas and feeling disadvantaged by society often tend to decline cooperation in surveys since they do not share either the social norm that survey participation is a civic duty, an interest in social exchange with interviewers, or an appreciation of this type of social-scientific research.

In addition to such macro-conditions, the paper at hand

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also investigates the timing of survey participation by considering time-varying circumstances at the macro level of a survey. Moving on to seasons (the macro level), Göritz (2014, pp. 158, 165) confirms the hypothesis that the starting rate—i.e. the proportion of invited panellists entering the first page of an online survey—is highest in winter months, while it is assumed that the retention (i.e. the completion rate among respondents who have started) is unaffected by the season in which the survey is carried out. However, it is found that the completion rate is higher in seasons other than winter (Göritz, 2014, p. 166). The seasonal differences in starting rates rest on the device and its use: since participating in web-based online surveys is primarily an indoor activity, it is assumed that this action is more likely to be performed in winter, while outdoor activities are more attractive in other seasons. During summer months, for example, "a higher share of panellists is on vacation and therefore less inclined or available to respond to a study request" (Göritz, 2014, p. 158). In another experiment, Potoski et al. (2015) found that surveys are at risk of temperature-induced participation. According to their findings, unusual temperatures seem decisive regarding who takes part in surveys: wealthier respondents are over-represented in especially cold and especially warm conditions.

However, it is still an open question whether this finding will be confirmed when, besides an individual's characteristics, the above-mentioned opportunity structures as well as the different and changing weather situations in different seasons and at different stages of the field period are taken into account. Due to logistical reasons, it is impossible to conduct all scientific surveys in winter, which would be the only adequate thing to do according to Göritz (2014) finding. Therefore, it is important to know whether—regardless of the season—"fine" weather situations are more likely to divert panellists from responding to a survey invitation than "bad" weather. Presumably, heavy rainfall and cold air temperatures enforce indoor activities and thereby lead to higher participation rates than the ones observed during periods of high temperatures and long hours of sunshine. The latter conditions are more likely to result in invitees postponing their survey participation and in their decreasing tendency to respond as time goes by. Even if they are intuitively plausible, such claims about the inclination of sampled target persons and the timing of survey participation have to be tested empirically.

Therefore, this contribution empirically analyses the following question: how do weather situations affect panellists' inclination to participate in a scientific online survey when controlling the seasons, stage of the field period, regional opportunity structure, and individuals' resources and abilities? This question about the eligible panellists' inclination and the timing of survey participation is answered in the context of a multi-wave panel study. Spell data on panellists' latency is used and event history analysis, which is suitable for combining micro- and macro-data in a longitudinal design, is applied.

2 Theoretical background, previous research, and hypotheses

For explaining the effect of the weather situation on the inclination of target persons to take part in an online survey, two theoretical approaches that have proved to be successful are considered (Fan & Yan, 2010, p. 136; Goyder, Boyer, & Martinelli, 2008). The first theoretical approach comprises several broad versions of rational action theories, such as the social exchange theory (Dillman, 2000; Dillman, Smyth, & Christian, 2014; Hox, de Leeuw, & Vogt, 1996), the leverage-salience theory (Groves & Couper, 1998; Groves, Singer, & Corning, 2000), or the theory of subjective utility (R. Becker, Möser, & Glauser, 2019; Esser, 1986, 1990). These versions all assume that an invited individual weighs the consequences of one action, such as requested survey participation, against the consequences of alternative activities belonging to the individual's perceived action set. Thereby, individuals calculate and evaluate such consequences based on the costs and benefits of the considered activities, as well as on the probability of success to receive the preferred benefits in an optimal way (Singer, 2011). Given that the subjective expected benefits and costs of different actions are in a balance so that the individual is indifferent about the survey participation, few changes in the rather diffuse benefits and costs could determine the decision between immediate survey participation, postponement of response, or refusal. In this case, for example, a prepaid monetary incentive could increase an individual's inclination to take part in the online survey, since subjective perceived benefits exceed the costs (Laurie & Lynn, 2009).

In another case, namely under "pleasant" weather conditions, the opportunity costs of survey participation—i.e. the benefits of activities forgone as a result of participation—increase due to the benefits of attractive outdoor activities. Therefore, an individual's survey participation is possibly at least delayed. Thus, when the weather encourages other leisure activities outside, it is likely that invitees show low inclination to respond to the researchers' request. As participation in a scientific survey is voluntary, individuals are free to decide if and at what point in time they will do so. In this respect, survey participation is a stochastic, i.e. time-dependent, process (Singer, 2006). In particular, an online survey is a self-administered survey mode providing the invited target persons with the opportunity to postpone starting to complete the questionnaire to another suitable point in time. In case of "fine weather", the participation can therefore easily be pushed to a day with an "unpleasant" weather situation.

In sum, concerning individuals' deliberative cost-benefit calculations regarding survey participation, it is assumed that—besides other preferences, obligations, and alternatives—the weather situation and the related alternative activities may function as incentives diverting invitees from survey participation. Therefore, the expectation is that a weather situation discouraging outdoor activities, such as a cold and rainy day, results in immediate survey participation and in a high participation rate. In contrast, a weather situation encouraging outdoor activities, such as a sunny and warm day, results in an individual's low inclination to participate in the survey and thus in a low participation rate (Hypothesis 1). In this sense, weather situations do not only affect the participation rate, but also the individuals' timing of their participation: while an "unpleasant" weather situation is assumed to be associated with "early" responses to a request for survey participation, the invitees retard their decision on survey participation in periods of "pleasant" weather situations (Hypothesis 2). As weather situations partially correlate with the seasons, according to the finding by Göritz (2014), individuals are expected to be more likely to participate in an online survey in winter than in other seasons (Hypothesis 3). However, since weather situations vary within the seasons, it is assumed that—net of the season—weather situations being perceived as an adverse circumstance for outdoor activities are correlated with a relatively high rate of early survey participation (Hypothesis 4). It is worth noting that, to test these hypotheses, a long-term panel study is needed, since multiple waves conducted at different seasons and in varying weather situations are necessary.

The second theoretical approach often used for explaining survey participation emphasizes heuristic and habitual decision-making in the sense of traditional action (Groves et al., 1992, p. 487). According to this approach, to cognitively define the situation initiated by the request for survey participation, bounded rational individuals make use of shortcuts and "rules of thumb" in the form of cognitive heuristics such as schemes, frames, scripts, and habits (Esser, 1990; Simon, 1959). On the one hand, given that panellists have had positive experiences with previous survey participation, have positive attitudes towards social-scientific surveys, share an interest in the survey topic, accept norms of reciprocity, show compliance with the legitimate authority conducting the survey, and are convinced they are able to complete the questionnaire without any effort, it is assumed they do not deliberate on costs and benefits but make an automatic-spontaneous decision in favour of the request (e.g. Stocké & Langfeldt, 2003). On the other hand, if invited target persons accept norms of reference groups that demonstrate negative attitudes and values towards scientific surveys, their swift refusal is often observed (Esser, 1986). In sum, according to this theoretical approach—in contrast with the above formulated assumptions based on rational action theory—neither an effect of the weather situation on the timing of response nor the response rate would be expected. If invited target persons have internalized the obligation to support the social sciences in line with a value-rational action, the confirmation of related values forces them to take part in the survey, mostly independent of any season or weather situation. However, in cases of conflict between different preferences, obligations, or unusual circumstances concerning survey participation and alternative activities, heuristic and habitual decision-making does not work. In these cases, individuals are nevertheless likely to deliberate with some cognitive effort the consequences of different alternative actions.

The question that now arises is which mechanism may be responsible for the effect of weather and season on survey participation in the case of automatic-spontaneous decision-making. Göritz (2014), for example, offers the ad hoc argument that moods induced by different weather situations or seasons might have an effect on the target person's decision to take part in the survey. Based on the weather-mood hypothesis by Watson (2000), this seems plausible. In addition, Connolly (2013, p. 457), reporting on the responsiveness of wellbeing to climate and transitory weather conditions, finds that life satisfaction decreases with the amount of rain on the day of the interview and that low temperatures increase happiness and reduce tiredness and stress. High temperatures, however, reduce happiness, which is consistent with the fact that the survey was conducted in summer. Keller et al. (2005) also find an association between weather and mood that is moderated by season and time spent outside: "pleasant" weather (high temperature and barometric pressure) is related to a better mood and better memory during the spring as time spent outside increased. They do not find this relationship at other times of the year, but "hotter" weather was associated with lower mood in the summertime (Keller et al., 2005, p. 724). Accounting for the findings by Potoski et al. (2015), saying that surveys are at risk of temperature-induced participation (particularly in the case of indifference to survey participation), the association between weather and survey participation can be assumed to be moderated by moods induced by season and weather situations. However, a study by Schmiedeberg and Schröder (2014) reports, in contrast to a previous study by Kämpfer and Mutz (2013), a non-existent effect of weather situations on answers to questions about life satisfaction.

Since the empirical findings on the weather-related mechanisms of survey participation are mixed for theoretical and methodological reasons, it is necessary to find other explanations. For example, it is expected that obligations—such as reciprocity or courtesy—initiated by the tailored prenotification or monetary incentive prepaid by the researcher neutralize any seasonal and meteorological effects on invitees' survey participation (Hypothesis 5). If individuals, in particular panellists having some experience with such gifts given by researchers, accept internalized norms such as social reciprocity, it is very likely that they will respond habitually to gifts—such as unconditionally prepaid money—in terms of a normative or norm-guided action if the selection of action could be classified as being cognitive-emotionally under the control of a social norm, such as accepted and legitimate reciprocity (Weber, 1922). They follow this norm independently of external influences, such as weather conditions or seasons (R. Becker et al., 2019).

According to the rational action approach, it is plausible that the effect of weather situations on survey participation is moderated by the regional opportunity structure (Hypothesis 6), meaning that the regional opportunity structure is an initial precondition for perceiving and realizing outdoor activities as an alternative to taking part in the online survey. This means that the incentives by weather situation become realized, providing there are opportunities for activities in the living environment deterring individuals from participation in a survey and that the benefits of these alternative actions are larger than for survey participation.

3 Data, variables, and statistical procedures

3.1 Data base

The empirical analysis uses longitudinal data from DAB (Determinanten der Ausbildungswahl und der Berufsbildungschancen) panel study (2020)—a multi-wave probability-based panel with a sequential mixed-mode design (R. Becker, Möser, Moser, & Glauser, 2020). The panellists are adolescents born around 1997 and living in the German-speaking cantons of Switzerland who have been interviewed mostly about their educational and occupational trajectories after compulsory schooling. The panel data is based on a random and 10 per cent stratified gross sample of 296 school classes, out of a total universe of 3,045 classes. A disproportional sampling of school classes from different school types, as well as a proportional sampling of school classes regarding the share of migrants within schools, were applied. At school level, a simple random sample of school classes was chosen. The initial probability sampling rests on data obtained from the Swiss Federal Statistical Office (FSO) (Glauser, 2015).

Between January 2012 and June 2020, eight waves were realized by sequential mixed-mode surveys and the Tailored Design Methods (R. Becker, Möser, Moser, & Glauser, 2020; Dillman et al., 2014). It was a push-to-web survey, while withholding alternative answering modes was implemented (Dillman, 2017; de Leeuw, 2018, p. 76; Lynn, 2020, p. 19). Considering costs and the participation rate, the first mode was a computer-assisted web-based interview (CAWI); the second mode was a computer-assisted telephone interview (CATI); and the third mode was a paper-and-pencil interview (PAPI). In the case of the web survey, the problem of undercoverage might be rather minor for this particular sample of young panellists. About 93 per cent of the Swiss population has access to the internet and uses it basically every day, but each of the interviewees of the DAB panel study (DAB = Determinanten der Ausbildungswahl und der Berufsbildungschancen) had daily access to the internet.

While in the first three waves interviews took place in the context of the panellists' school classes, they have been followed since the fourth wave (conducted in October and November 2014) after leaving compulsory school. The fifth wave took place from June to August 2016, Wave 6 from May to June 2017, Wave 7 in the same months one year later, and Wave 8 was realized from May to June 2020. In each of the waves (i.e. Waves 4 to 8) considered in this analysis, between 2,500 and 2,900 panellists were pushed to participate in the online surveys. To improve the response rate, they got an unconditional prepaid incentive (voucher, ballpoint pen, or a 10 Swiss Francs banknote in cash) since they are effective for push-to-web surveys (R. Becker et al., 2019; Göritz, 2008; Singer & Ye, 2013). If one considers the other survey modes as well, the total participation rate remained rather constant at the level of about 80 per cent across the waves (Table 1).

In this study, the empirical analysis—limited to Waves 4 to 8—is focused on the first mode of data collection (CAWI) only and, for methodological reasons, the observation window is standardized to four weeks—i.e. exactly 28 days (R. Becker et al., 2019). For the five waves (4 to 8), 13,220 spells were available for the analysis. Since time stamps—collected automatically by the survey software Unipark—indicate the exact time reference of the panellists starting to complete the online questionnaire, it is possible to calculate the exact duration of episodes from the start of the field period until the start of participation on a daily or hourly basis (e.g. Durrant, D'Arrigo, & Steele, 2013). Furthermore, the spell data set provides dynamic longitudinal estimations based on techniques of event history data (Allison, 2014; R. Becker & Glauser, 2018; R. Becker & Mehlkop, 2011; R. Becker et al., 2019; Blossfeld, Rohwer, & Schneider, 2019; Rabe-Hesketh & Skrondal, 2012; Steele, 2008).

3.2 Statistical procedures and the dependent variable

Since the time-dependent likelihood of participation in the CAWI of the DAB panel study is the dependent variable, event history analysis is an adequate statistical approach for estimating the distribution of the waiting times from survey launch until the invitees' response. In general, the participation rate is defined by the ratio of contactable units and their response in terms of starting with the completion of the online questionnaire (RR2 according to AAPOR (The American Association for Public Opinion Research), 2015, p. 52; Bethlehem, Cobben, & Schouten, 2011, pp. 11–12; Singer, 2006, p. 637). Due to the episode-oriented questionnaire on the young panellists' life history, it is difficult to measure ex-

Table 1
Samples and response in the DAB panel

	Wave 4 Oct–Nov 2014	Wave 5 Jun–Aug 2016	Wave 6 May–Jun 2017	Wave 7 May–Jun 2018	Wave 8 May–Jun 2020
Sample size					
Gross sample	3,526	2,864	2,738	2,496	2,496
Contactable individuals	2,655	2,800	2,720	2,489	2,493
Incentives					
Incentive	voucher	voucher	ballpoint pen	money	money
Realized interviews					
Individuals	2,236	2,229	2,061	1,958	1,947
of whom: online	1,227	1,330	1,375	1,646	1,815
CATI and PAPI	1,009	899	686	312	132
Response rate					
Contactable individuals	84%	80%	76%	79%	78%
Online	46%	48%	51%	66%	73%
CATI and PAPI	38%	32%	26%	13%	5%

Own calculations, see R. Becker, Möser, Moser, and Glauser (2020)

act completion rates among respondents. For data collection with an event history design, it is uncertain if respondents completed the questionnaire or omitted some of the episodes in their educational and occupational trajectory. Given this uncertainty, about 80 per cent of the respondents completed the questionnaire in the CAWI mode (R. Becker & Glauser, 2018).

The aim of these statistical methods is the dynamic multi-level analysis of longitudinal data regarding the occurrence and timing of stochastic events, such as the eligible panellists starting the CAWI depending on weather situation and other theoretically interesting covariates. For estimating the time-dependent likelihood of survey participation as a stochastic and time-variant function of individual resources, survey settings, and exogenous factors such as the weather situation, the hazard rate $r(t)$ is defined as the marginal value of the conditional probability of the start of completing the questionnaire in the web-based online survey in the time interval $(t, t + \delta t)$, given that this event has not occurred before time t (Blossfeld et al., 2019, p. 29; Steele, 2008, p. 7). Using this statistical procedure, it is possible to reveal causal impacts on the occurrence of an event such as survey participation (R. Becker et al., 2019).

To consider the impact of time-varying covariates, such as changing weather situations or the seasons in which the survey took place, the technique of episode splitting is applied. This means that, for each of the panellists, their initial waiting time is split into sub-episodes on a daily basis. For each of these sub-episodes, a constant hazard rate is assumed. Thus, the hazard rate will be estimated on the basis of an exponential distribution: $r(t|x(t)) = \exp(\beta' x(t))$, whereby $x(t)$ is the time-dependent vector of exogenous variables whose unknown coefficients β have to be estimated. Based on the exponential model, it is possible to model step functions that display the empirically observed hazard function for the entire process until participation.

Employing the technique of episode splitting and the estimation of the exponential mode, the statistical software package Stata (Version 16) is used (Kohler & Kreuter, 2012). The stsplit procedure is suited for the episode splitting and the streg procedure for the dynamic multi-level estimations (Blossfeld et al., 2019).

3.3 Independent variables

The main exogenous variable at the macro level is the daily information on the weather situation during the field periods of the different survey waves. The following indicators measured on a daily basis are considered: average air temperature by day (in degrees centigrade); relative humidity (daily average in per cent); rainfall (daily average in millimetres); duration of sunshine (in hours a day); and barometric pressure (in hectopascals). These time-varying indicators are taken from the SwissMeteo website of the Federal Office of Meteorology and Climatology (2020).

To reduce complexity and multicollinearity in the time series, confirmatory factor analysis was applied to these four time series separately for each wave (Harrington, 2009). The factor was extracted using the main component method and orthogonal factor rotation. It explains almost 91 per cent of the variance in the weather situation of October/November 2014, 90 per cent in May/June 2016, about 83 per cent in April/May 2017, almost 93 per cent in May 2018, and about 94 per cent of the variance in the weather situation of May

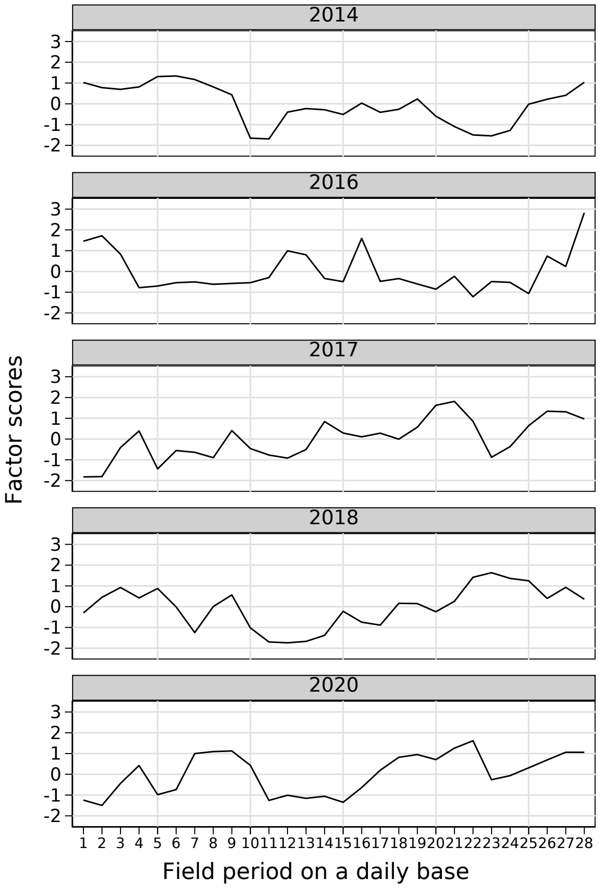

Figure 1. Weather situations in the DAB field period across five waves

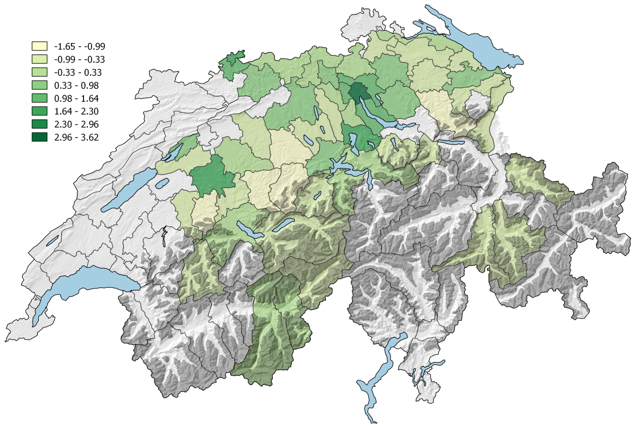

Figure 2. Distribution of the scaling variable representing regional opportunity structures (Glauser & Becker, 2016, p. 20)

2020. Figure 1 depicts the development of the weather situation: the higher the factor scores, the higher the temperatures and the longer the duration of sunshine. Lower factor scores indicate uncomfortable weather—i.e. higher values for humidity and rainfall.

Furthermore, the different seasons in which the fieldwork took place are considered using dummy variables. They differentiate between spring (Waves 6–8), autumn (Wave 4), and summer (Wave 5), the latter being the reference category. Alternatively, the panel waves (and the prepaid incentives included) are captured by dummy variables.

The opportunity structure of the region in which the panellists live is taken into account to consider competing factors possibly also diverting the invitees from starting the questionnaire. From a theoretical point of view, they are related to the panellists' opportunity costs of survey participation. To account for regional opportunity structures, macro-data from the FSO at regional levels are used (Glauser & Becker, 2016).

To indicate the regional opportunity structure, to reduce its complexity, and to control the high correlation of the regional contextual characteristics, factor scores were extracted from these data. The total of 106 regions is characterized by a certain spatial homogeneity, reflecting the principle of small, partially cross-cantonal labour market areas with functional orientation towards centred and peripheral opportunities and living standards in addition to urbanicity, population density, and lack of social cohesion (Couper & Groves, 1996, p. 174). The distribution of the factor scores across the German-speaking cantons is depicted in Figure 2 (Glauser & Becker, 2016, p. 20).

To control social heterogeneity in the sample at the micro level, different time-constant socio-demographic characteristics of the panellists are considered. For one, this includes the panellists' gender (reference category: male), as well as their social origin as a proxy for the target persons' social context and economic resources, social integration, and environment, as well as attitudes and values in favour of survey participation (R. Becker et al., 2019; Stocké & Becker, 2004; Groves & Couper, 1998, p. 30; Couper & Groves, 1996, p. 174). The social origin is captured by the class scheme suggested by Erikson and Goldthorpe (1992).

Additionally, the interviewees' cognitive resources and language proficiency—measured by their standardized grade point average in German language—as a proxy for institutionally attested language-speaking ability and intelligence, as well as the school type in which they were enrolled, are included. They also indicate the transaction costs and cognitive burden of survey participation. The school type is also a proxy for educational level, correlated with the appreciation of the utility of social-scientific research and information-gathering activities (Groves & Couper, 1998, p. 128).

Unobserved heterogeneity based on the reluctance of individuals to start the questionnaire, on individuals' attitudes

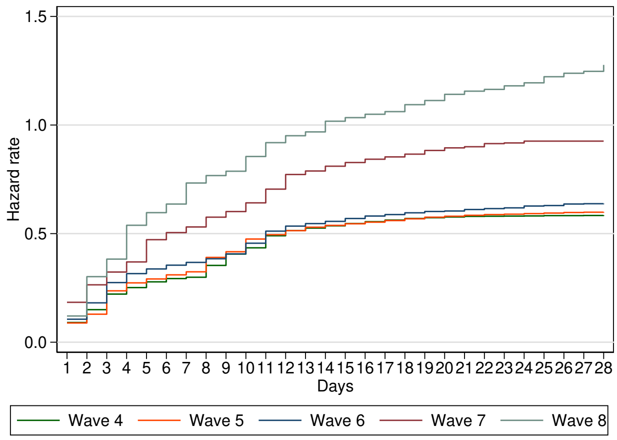

Figure 3. Nelson-Aalen cumulative hazard estimates

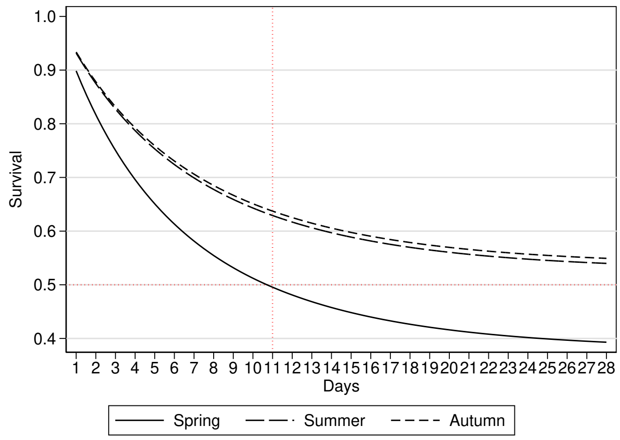

Figure 4. Gompertz-Makeham distribution of survivals in terms of seasons

towards scientific surveys, or on moods and emotions relating to the weather situation is indicated by the panellists' latency between the invitation and starting the questionnaire on a daily basis.

The descriptive statistics on the independent variables are documented in Table A-1 in the appendix. They are calculated for the data set with episode splitting.

4 Empirical results

4.1 Description of the timing of survey participation

First, patterns of the timing of participation in the online surveys are described. Figure 3 shows the cumulated hazard rates for the different panel waves. It is obvious that panellists' responses were more likely and occurred much earlier in Waves 6–8, conducted in the years 2017, 2018, and 2020 during spring. In Waves 4 and 5, realized in autumn 2014 and summer 2016, the hazard rates were much lower and it took much more time for panellists to respond to the request to start completing the online questionnaire.

The differences between the hazard rates for the three most recent waves that took place in the spring months are significant. It still has to be analysed whether these differences in hazard rates are associated with the weather situation or with alternative explanatory factors.

In the next step, the timing patterns of participation are analysed explicitly regarding the season in which they took place. In Figure 4, they are depicted as survivals curves. Again, the seasonal differences in survey participation become obvious. For example, it was 11 days before 50 per cent of the panellists invited to take part in the spring waves (see reference lines) had actually taken part, while for the other seasonal surveys there was no median value for the online survey mode.

After 28 days, 61 per cent of invitees had responded to the spring surveys; in contrast, after the same amount of time, 46 per cent of eligible panellists had taken part in the summer months and 45 per cent in the autumn survey. While it took four days for a third of the panellists in the spring surveys to start completing the online questionnaire, just a quarter of them responded in the other seasons over the same time interval. In sum, the timing and magnitude of survey participation were significantly different depending on the seasons usually providing different weather situations. For the online mode, tests for the equality of survivor functions such as Log-rank or Wilcoxon (Breslow) reveal that the survival curves were significantly different for each of the stages in the field periods, each lasting four weeks. The conclusion that these differences are strictly seasonal has to be made cautiously, since the winter season is not considered in this study.

4.2 Impact of the weather situation on survey participation

Utilizing a dynamic multivariate exponential model, the weather situation is considered as a time-varying covariate (Table 2). Indeed, there is a significant meteorological effect on the likelihood and timing of survey participation. In line with Hypothesis 1, "unpleasant" weather (cold and rainy) increases the likelihood of participation, while the inclination for survey participation is much lower during "pleasant" weather periods consisting of sunny and warm days (Model 1).

Indeed, in line with Hypothesis 2, "pleasant" weather periods result in panellists postponing their response. An increase of one weather factor score decreases the "chance" of participation by about 15 per cent. This "chance" is calculated by subtracting one from the hazard ratio exp(−0.167) and multiplying the result with 100 per cent.

This meteorological effect remains strong when other covariates are controlled (Models 2–4). For example, it is ex-

Table 2

Time-dependent impact of weather situation on the participation at the DAB panel study (Waves 4–8)

	(1) β, (S.E.)	(2) β, (S.E.)	(3) β, (S.E.)	(4) β, (S.E.)	(5[b]) β, (S.E.)
Macro-factors[a]					
Weather situation	–0.167***	–0.143***	–0.052***	–0.029*	–0.059
	(0.012)	(0.012)	(0.013)	(0.013)	(0.015)***
Regional opportunity structure	–0.044***	–0.047**	–0.052***	–0.050***	–0.048
	(0.012)	(0.012)	(0.012)	(0.012)	(0.014)***
Spring (vs summer)	-	-	-	0.364***	0.190
	-	-	-	(0.033)	(0.036)***
Autumn (vs summer)	-	-	-	–0.038	–0.032
	-	-	-	(0.040)	(0.040)
Wave, incentive (Ref.: Wave 4, voucher)[a]					
Wave 5, voucher	-	0.028	0.032	-	-
	-	(0.040)	(0.040)	-	-
Wave 6, ballpoint pen	-	0.074	0.049	-	-
	-	(0.040)	(0.044)	-	-
Wave 7, cash	-	0.544***	0.426***	-	-
	-	(0.039)	(0.040)	-	-
Wave 8, cash	-	0.886***	0.661***	-	-
	-	(0.037)	(0.040)	-	-
Field period[a]					
Duration in days after survey launch	-	-	–0.125***	–0.127***	–0.134
	-	-	(0.002)	(0.002)	(0.003)***
Social origin (Ref.: missing value)					
Upper service class	-	-	0.277***	0.285***	0.298
	-	-	(0.047)	(0.047)	(0.055)***
Lower service class	-	-	0.281***	0.285***	0.309
	-	-	(0.044)	(0.044)	(0.052)***
Routine non-manual employees	-	-	0.264***	0.270***	0.292
	-	-	(0.043)	(0.043)	(0.050)***
Farmers, small proprietors		-	0.244***	0.248***	0.263
	-	-	(0.059)	(0.059)	(0.069)***
Foreman, skilled manual worker	-	-	0.109*	0.116*	0.123
	-	-	(0.047)	(0.047)	(0.055)*
Semi- and unskilled manual workers	-	-	0.110	0.119	0.116
	-	-	(0.064)	(0.064)	(0.075)
School type (Ref.: missing value)					
Basic requirements	-	-	–0.326***	–0.316***	–0.316
	-	-	(0.046)	(0.046)	(0.054)***
Extended requirements	-	-	0.199***	0.211***	0.241
	-	-	(0.041)	(0.041)	(0.047)***
Pre-gymnasium	-	-	0.617***	0.624***	0.650
	-	-	(0.044)	(0.044)	(0.051)***
Individual characteristics					
Language proficiency	-	-	0.141***	0.153***	0.162
	-	-	(0.013)	(0.013)	(0.016)***
Female (Ref.: male)	-	-	0.260***	0.256***	0.268
	-	-	(0.024)	(0.024)	(0.028)***
Constant	–3.388***	–3.680***	–3.047***	–3.023***	–3.017
	(0.012)	(0.029)	(0.055)	(0.051)	(0.057)***
Number of episodes	210,977	210,977	210,977	210,977	181,914
Number of cases	13,220	13,220	13,220	13,220	10,727
Number of events	7,187	7,187	7,187	7,187	5,368
LR chi2 (d.f.)	198.57 (2)	1,097.43 (6)	7,490.03 (18)	7,200.76 (16)	5,626.00 (16)

Estimated by piecewise constant exponential model

[a] Time-varying covariates [b] Without Wave 8

* $p < 0.05$ ** $p < 0.01$ *** $p < 0.001$

pected that the meteorological effect is associated with alternative outdoor activities that are in turn associated with regional opportunity structures. In line with Hypothesis 6, stating that the opportunity structure is an initial precondition for perceiving and realizing outdoor activities as an alternative to taking part in the online survey, a significant effect of the regional opportunity structure on survey participation is detected (Models 2–4). The higher the urbanicity and living standard of the regional context of panellists, the lower their inclination is to take part in the survey, even despite the urban-rural divide of internet access. An increase of the regional opportunity structure by one factor score lowers the "chance" of participation by about $(\exp(-0.047)-1)\cdot 100 = 5$ per cent. In general, this result is in line with other studies revealing that the participation rates are higher in rural than in metropolitan areas.

In addition, Hypothesis 6 is tested again by including the interaction between the weather situation and the regional opportunity structure (Figure 5a). While the main effects remain statistically significant, the interaction between the macro-factors is insignificant. This means that both the weather situation and the regional opportunity structure provide independent influences on survey participation.

These macro-effects are constant when additionally accounting for the prepaid incentives given to the panellists (Models 2 and 3). Therefore, Hypothesis 5, expecting that obligations—such as reciprocity or courtesy—initiated by monetary incentives prepaid by the researcher neutralize any seasonal and meteorological effects on invitees' survey participation, is not confirmed. Independent of other influences, cash as an incentive results in the earlier and higher participation rates of panellists.

Furthermore, the effect of the weather situation remains significant when the season in which the surveys took place is controlled (Model 4). Hypothesis 4, expecting that—net of the season—an "unpleasant" weather situation is correlated with a relatively high rate of early survey participation, is also confirmed. It is worth noting that the participation in a panel survey is most likely in spring (see left panel in Figure 5b).

Hypothesis 4 is retested in an additional estimation since one could expect an interaction effect of the weather situation and the season on survey participation (Figure 5b). This interaction effect would signify that the meteorological effect is different for different seasons. This is indeed the case: on the one hand, the more "pleasant" the weather in spring compared to the weather in summer, the less likely invitees are to take part in the online survey. On the other hand, the more "pleasant" the weather is in autumn compared to the weather in the summertime, the higher the participation rate in autumn in contrast to summer.

Finally, it has to be emphasized that these macro-effects on survey participation remain constant even after controlling the panellists' characteristics (Models 3 and 4). The longer the panellists retard their participation after the survey launch, the less likely they are to start the questionnaire at a later point in time of the field period. The more the socioeconomic resources (indicated by the parental class position), the earlier and more likely the invitees are to start completing the questionnaire. The higher their abilities and achievements (measured by enrolment in a school type with a special requirement and GPA indicating language proficiency), the higher their inclination and speed of reaction to the request for survey participation. In line with other studies, a gender difference is found, confirming again that female panellists are more likely to take part in surveys than their male counterparts (e.g. Keusch, 2015).

Due to the coincidence of the coronavirus pandemic and the field period in 2020, a direct COVID-19 pandemic effect, as well as an indirect effect of non-pharmaceutical official orders and arrangements related to the SARS-CoV-2 outbreak, resulting in the public shutdown, on the survey participation in Wave 8 is considered by omitting this survey (Model 5). Since the findings are stable instead of excluding the most recent wave, the previous results are characterized to be robust. However, possible COVID-19 pandemic effects on participation in Wave 8 of the DAB panel study have to be analysed in detail (R. Becker, Glauser, & Möser, 2020).

4.3 Characteristics of the weather situation and survey participation

Finally, it is analysed which of the characteristics of the weather situation are relevant for explaining the timing and rate of survey participation (Table 3). On the one hand, panellists are more likely to take part in the survey on rainy days: the heavier the rainfall, the higher the pace and magnitude of participation (Models 1–4). An increase in rainfall by one unit results in an increased survey participation rate of $(\exp(0.295) - 1) \cdot 100 = 34$ per cent. On the other hand, "pleasant" weather characteristics result in lower speed and a lower rate of participation: the longer the sun shines during the day and the higher the air temperature, the relative humidity, and the barometric pressure, the lower the survey participation rate across the field period.

The significant effects of the weather characteristics on survey participation are valid, since the effects of panel waves remain significant (Models 1 and 2). This means that meteorological effects do not partial out the effects of the waves—i.e. they are no proxies for impacts related to the waves, such as panellists' experience or other unobserved heterogeneities. If one takes the seasons into account, the effect of the weather characteristics (Models 3–4) and the typical effect of seasons on survey participation (see Model 4 in Table 3 and Figure 5b) are reproduced.

However, a closer look at the development of rainfall during the different field periods (Figure 6) reveals that the effect

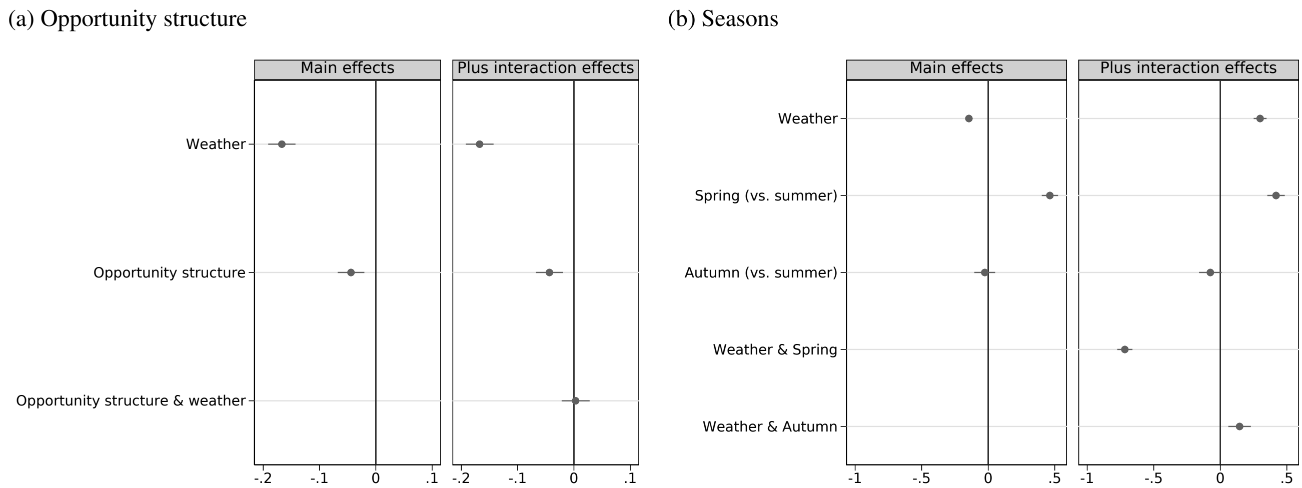

Figure 5. Effect of weather situations and . . . on survey participation (β-coefficients)

of the intensity of rainfall on both the timing and the rate of survey participation depends on its timing within the field period. It makes a difference whether heavy rainfall occurs at the initial stage of the fieldwork or at later stages after survey launch.

Heavy rainfall at the initial stage is associated with swift participation and high response rates; this is true for the field periods in the three last waves realized during the spring of 2017, 2018, and 2020. There was no or less rainfall at the initial stage of the waves conducted in autumn 2014 and summer 2016.

To make this observation watertight, Figure 7a shows the interaction effect of rainfall and seasons on survey participation. Heavy rainfall at a very early stage of the fieldwork contributes to higher participation rates in spring and autumn. The magnitude of the interaction effects of seasons and rainfall exceeds the main effects.

In addition, the interaction between rainfall and the duration of fieldwork (in days since survey launch) provides support for the importance of the timing of the rainfall. As depicted in Figure 7b, rainfall is positively associated with survey participation, while the increase in the participation rate significantly fades the longer the field period lasts. The negative, but minor, interaction effect confirms the assumption that the rainfall effect is largest in the initial stage of the field period. Heavy rainfall around the survey launch indeed works in favour of a high speed and rate of survey participation.

Overall, these results are constant when an individual's social origin, school type, achievement, and gender are additionally accounted for (Model 2; not depicted). It is noteworthy that the effect of opportunity structure on participation in the online survey is still significant and negative (Models 1–4).

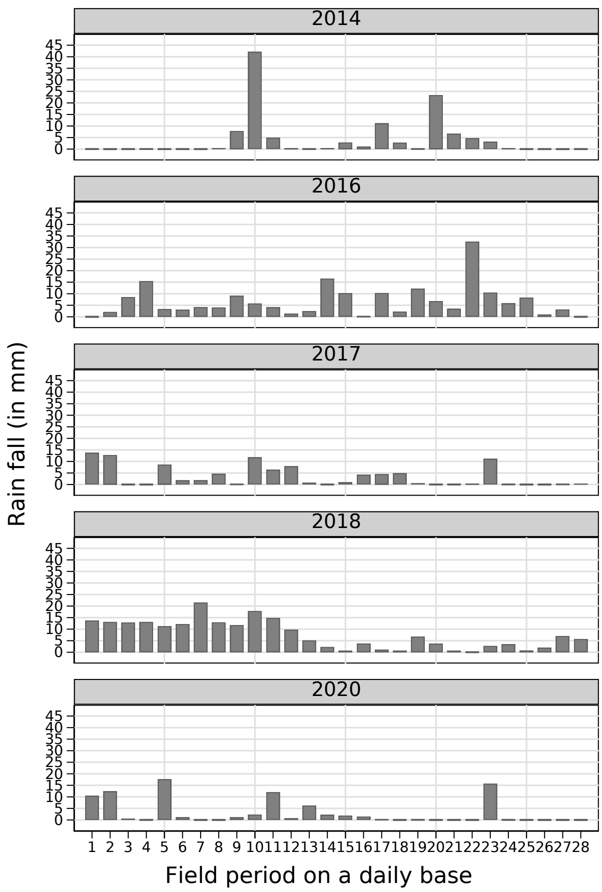

Figure 6. Development of rainfall in field periods

Table 3
Time-dependent impact of the weather situation on participation in the DAB panel study (Waves 4–8)

	(1) β, (S.E.)	(2[b]) β, (S.E.)	(3) β, (S.E.)	(4[b]) β, (S.E.)
Macro-factors[a]				
Rainfall (in mm)	0.295***	0.279***	0.299***	0.281***
	(0.013)	(0.013)	(0.013)	(0.013)
Sunshine duration (in hours)	–0.150***	–0.145***	–0.174***	–0.171***
	(0.027)	(0.027)	(0.027)	(0.027)
Air temperature the day (in Celsius)	–0.385***	–0.359***	–0.363***	–0.339***
	(0.018)	(0.018)	(0.018)	(0.018)
Relative humidity (in %)	–0.597***	–0.567***	–0.598***	–0.570***
	(0.029)	(0.029)	(0.029)	(0.029)
Barometric pressure (in hectopascal)	–0.074***	–0.070***	–0.061***	–0.061***
	(0.013)	(0.013)	(0.013)	(0.013)
Spring (vs summer)	-	-	0.497***	0.473***
	-	-	(0.031)	(0.031)
Autumn (vs summer)	-	-	–0.043	–0.066
	-	-	(0.040)	(0.040)
Regional opportunity structure	–0.045***	–0.060***	–0.043***	–0.057***
	(0.012)	(0.012)	(0.012)	(0.012)
Wave, incentive (Ref.: Wave 4, voucher)[a]				
Wave 5, voucher	0.038	0.061	-	-
	(0.040)	(0.040)	-	-
Wave 6, ballpoint pen	0.123**	0.140***	-	-
	(0.040)	(0.040)	-	-
Wave 7, cash	0.562***	0.545***	-	-
	(0.039)	(0.039)	-	-
Wave 8, cash	0.959***	0.953***	-	-
	(0.037)	(0.037)	-	-
Constant	–3.779***	–4.297***	–3.737***	–4.249***
	(0.030)	(0.053)	(0.028)	(0.049)
Number of episodes	210,977	210,977	210,977	210,977
Number of cases	13,220	13,220	13,220	13,220
Number of events	7,187	7,187	7,187	7,187
LR chi2 (d.f.)	2,175.53 (10)	3,844.16 (21)	1,637.08 (8)	3,337.65 (19)

Estimated by piecewise constant exponential model
[a] Time-varying covariates [b] Controlled for social origin, school type, and language proficiency
* $p < 0.05$ ** $p < 0.01$ *** $p < 0.001$

5 Summary and conclusions

The aim of this empirical study was to analyse how different weather situations affect the inclination of panellists to participate in a scientific online panel survey by controlling seasons, regional opportunity structures, and individuals' resources and abilities. On the one hand, this provides an indirect test of different theoretical approaches seeking to explain why individuals participate in web-based online surveys or refuse the request for response. On the other hand, in the present dynamic longitudinal revealed preference analysis, the focus lies on under-investigated time-dependent macro-level-impacts (such as the weather situation, seasons, or the rural-urban divide) on the timing of survey participation and response rate. The macro- and micro-levels have been linked by connecting time series on weather situations during the field periods of a multi-wave panel study and event-oriented data on the panellists' participation in multiple waves.

Applying techniques of event-history data analysis, the findings indicate that "pleasant" weather situations have adverse effects on the timing of survey participation, while "unpleasant" weather situations result in early responses and high participation rates. Furthermore, the earliest and highest participation rates were observed during the spring months in

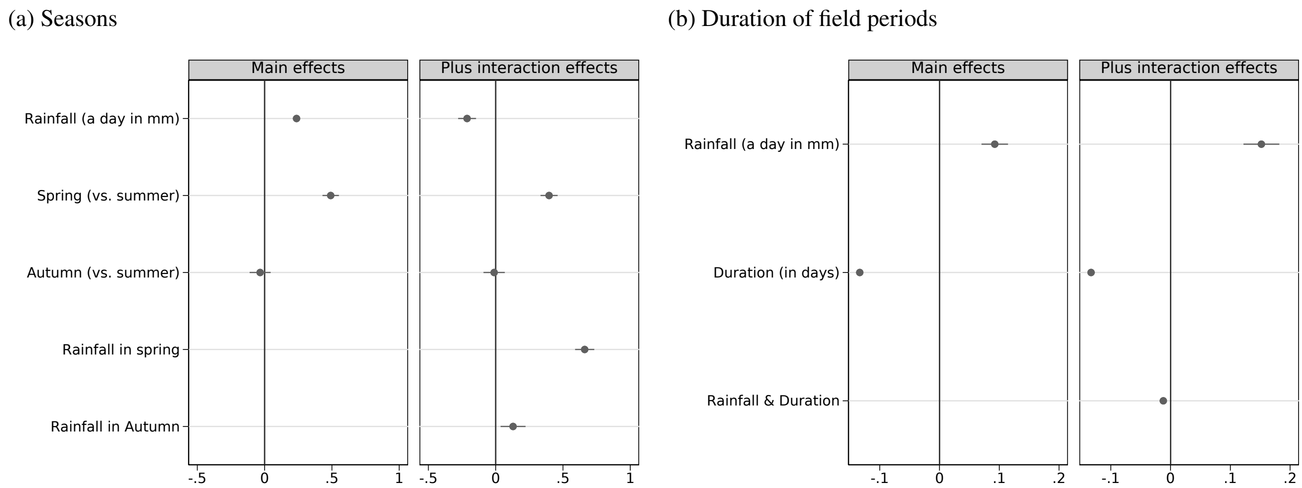

Figure 7. Interaction effects of rainfall in field periods and . . . (β-coefficients)

contrast to summer and autumn. These effects are not associated with the regional opportunity structures providing opportunities for outdoor activities, possibly diverting invited panellists from completing the online questionnaire. The interactions between weather, seasons, and regional opportunities were insignificant. However, there was an association between weather situation and season. While in spring, the speed and rate of survey participation developed positively during rainy and cold periods, the panellists were more likely to take part in the online survey during sunny and warm periods in the autumn months. Furthermore, the results pointed to heavy rainfall at survey launch being associated with high speed and rate of survey participation. This is especially true for the spring period and—to a lesser extent—for the autumn months. In sum, it is fair to say that rather moderate weather situations are most efficient for conducting an online survey in terms of rapid response and high participation rates. For the management of web-based online surveys, the recommendation is therefore to start the field period in times of heavy rainfall if one is interested in high participation rates and short field periods.

However, the peculiar development in Wave 8 realized in May 2020 could be associated with the coronavirus pandemic of COVID-19, resulting in the public shutdown specified by a governmental regulation declared on 13 March 2020 until 10 May 2020. If this public shutdown—organized to avoid the spread of the infectious disease caused by SARS-CoV-2—minimized the opportunities for outdoor activities, it may have resulted in swift responses after the survey launch on 1 May 2020 and to the extraordinarily high participation rates, which have to be investigated in detail (Figure 3).

In sum, the social mechanism behind the association between weather situation and survey participation could not be revealed due to lack of information. On the one hand, it seems plausible that a “pleasant” weather situation encourages outdoor activities, while the start of completing an online questionnaire in a push-to-web survey requires “unpleasant” weather. On the other hand, moods could also be an important moderator for this association; but they are in conflict with obligations initiated by pre-notification, prepaid incentives, and respondents’ attitudes to social-scientific surveys. However, the essential precondition for an answer to this open question is the analytical-empirical test of several approaches, which attempts to deliver a mechanism-based explanation of survey participation and unit non-response.

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The data of the first seven waves are available as Scientific Use Files (SUF) at FORS in Lausanne and can be found in the online catalogue under the reference number 10773.[1] The SUF for Wave 8 will be available in 2021. The meta-data on field period, the time series on weather situations as well as the data on regional opportunity structures can be requested from the author. The data set and syntax file is available on the website of SRM.

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Appendix
Tables

Table A1
Descriptive statistics

	n	Mean	Std. dev.	Minimum	Maximum
Time-varying variables					
Weather situation	210,977	−0.03	0.97	−1.82	2.83
Rainfall (in mm)	210,977	5.37	6.82	0.00	42.14
Sunshine duration (in hours)	210,977	4.89	3.77	0	13.25
Air temperature the day (in Celsius)	210,977	6.93	3.99	−3.30	16.66
Relative humidity (in %)	210,977	79.40	10.55	51.31	96.31
Barometric pressure (in hectopascal)	210,977	1015.77	6.39	996.24	1033.17
Spring	111,662	52.87%	-	0	1
Summer	51,444	24.36%	-	0	1
Autumn	47,871	22.67%	-	0	1
Seasons	210,977	100.00%	-	-	-
Regional opportunity structure	210,977	0.24	0.99	−1.65	3.62
Duration in days after survey launch	210,977	11.72	8.25	0	27
Wave 4	47,871	22.69%	-	0	1
Wave 5	51,444	24.38%	-	0	1
Wave 6	47,212	22.38%	-	0	1
Wave 7	35,387	16.77%	-	0	1
Wave 8	29,063	13.78%	-	0	1
Waves 4–8	210,977	100.00%	-	-	-
Time-constant variables					
Social origin	-	-	-	-	-
Upper service class	27,725	13.14%	-	0	1
Lower service class	36,651	17.37%	-	0	1
Routine non-manual employees	48,978	23.21%	-	0	1
Farmers, small proprietors	12,739	6.04%	-	0	1
Foreman, skilled manual worker	37,889	17.96%	-	0	1
Semi- and unskilled manual workers	13,021	6.17%	-	0	1
Missing value	33,974	16.10%	-	0	1
EGP classes	210,977	100.00%	-	-	-
School type	-	-	-	-	-
Basic requirements	70,399	33.37%	-	0	1
Extended requirements	86,652	41.07%	-	0	1
Pre-gymnasium	22,434	10.63%	-	0	1
Missing value	31,942	14.93%	-	0	1
School types	210,977	100.00%	-	-	-
Individual characteristics					
Language proficiency	210,977	−0.09	1.00	−3.38	1.46
Female	96,462	45.72%	-	0	1
Male	114,515	54.28%	-	0	1
Gender	210,977	100.00%	-	-	-